A Novel Approach for Change Detection in High Resolution Images

Synopsis

Submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

in

Electronics & Communication Engineering

Submitted by

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While presenting this piece of synopsis of my research work, I take this opportunity to express my thanks to the people who have encouraged and inspired me to take the challenge of doing the research work leading to the Degree of Ph.D.

Firstly, I would like to show my heartfelt gratitude to my Supervisors Dr. Kuldip Pahwa, Prof. & Co-Ordinator, ECE Department, MMEC, M.M. University Mullana for his tremendous support and help. Without the wise counsel and able guidance, it would have been impossible to complete the synopsis in this manner I am grateful for his constant support and help. I am also thankful to Dr. H. P. Sinha, Head, Electronics and Communication Department, MMEC, M.M. University Mullana for his tremendous and help.

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Abstract

Change detection is the process of automatically identifying and analyzing regions that have undergone spatial or spectral changes from high resolution images. Detecting and representing change provides valuable information of the possible transformations a given scene has suffered over time. Change detection in sequences of high resolution images is complicated by the fact that change can occur in the temporal and/or spectral domains.

The objective is to developed an algorithm to for change detection in high resolution images. The basis of this strategy will be to measure changes in high resolution images and then generate alarms subject to the timings and extent of change detected. The algorithm will monitor and record the changes detected, and compare the extent of change detected with a threshold value; to generate warning alarms. The number and rate of change of events per unit time and per unit pixels will be evaluated. The number of incorrect pixels selected and thus giving false alarms will also be investigated.

The algorithms will be implemented using Matlab, and its performances will be presented in terms of false alarms and missed changes.

Keywords: Unsupervised, Change Detection.

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1. Introduction

This section presents the introduction to image processing, remote sensing and change detection necessary for the understanding of the fundamental aspects of the research reported to be done through this synopsis. These are discussed below.

1.1 Image Processing

Image processing is any form of signal processing for which the input is an image, such as a photograph or video frame; the output of image processing may be either an image or a set of characteristics or parameters related to the image. Most image-processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it. Image processing usually refers to digital image processing, but optical and analog image processing also are possible. The processed images may be of low resolution, high resolution such as SAR images or hyperspectral images.

1.2 Spectral sensing

Multispectral remote sensing involves the acquisition of visible, near infrared, and short-wave infrared images in several broad wavelength bands. Different materials reflect and absorb differently at different wavelengths.

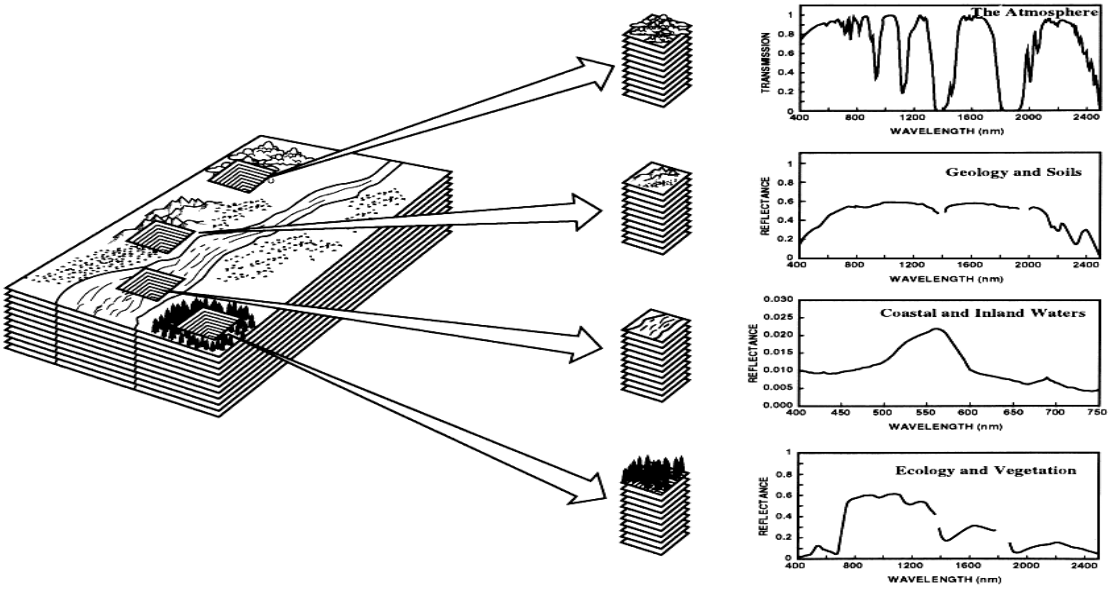

Figure 1.1: An example of hyperspectral imaging [1].

As such, it is possible to differentiate among materials by their spectral reflectance signatures as observed in these remotely sensed images, whereas direct identification is usually not possible. NASA's Landsat, one of the more common multispectral imagers, is widely used for monitoring a wide range of landscape scale properties. Hyperspectral imaging systems acquire images in over one hundred contiguous spectral bands. While multispectral imagery is useful to discriminate land surface features and landscape patterns, hyperspectral imagery allows for identification and characterization of materials. In addition to mapping distribution of materials, assessment of individual pixels is often useful for detecting unique objects in the scene [1].

1.3 Image Classification

Digital image classification uses the spectral information represented by the digital numbers in one or more spectral bands, and attempts to classify each individual pixel based on this spectral information. This type of classification is termed spectral pattern recognition. In either case, the objective is to assign all pixels in the image to particular classes or themes (e.g. water, coniferous forest, deciduous forest, corn, wheat, etc.)[2]. The resulting classified image is comprised of a mosaic of pixels, each of which belongs to a particular theme, and is essentially a thematic map of the original image, as can be seen in Figure 1.2 below.

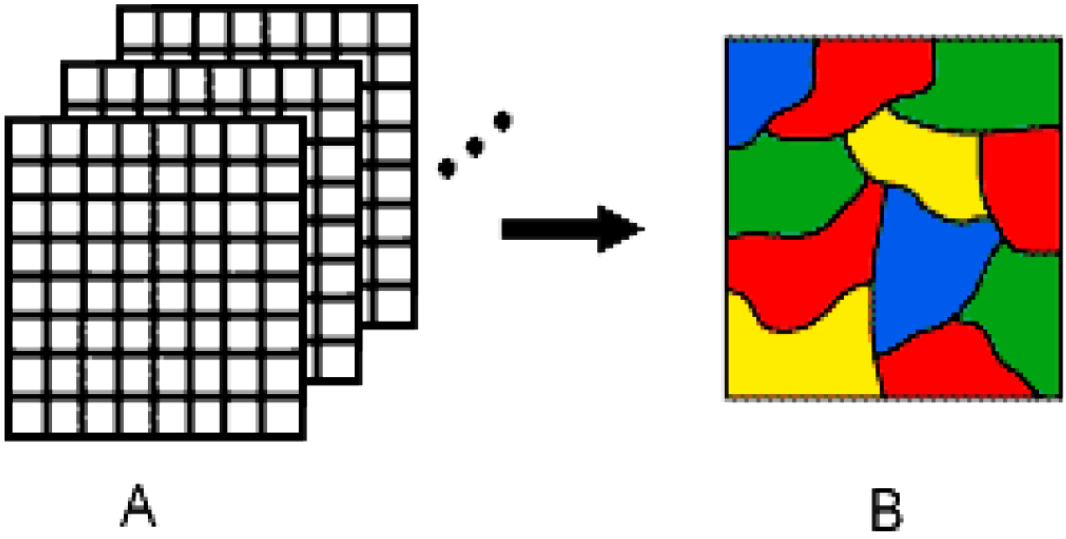

Figure 1.2: Image classification (From CCRS Website).

Common classification procedures can be broken down into two broad subdivisions based on the method used: supervised classification and unsupervised classification. These are described below.

1.3.1 Supervised classification

Supervised classifications require up-front knowledge of the scene area in order to provide the computer with unique material groups or what are called "training classes". Regions containing a material of interest within a scene are delineated graphically and stored for use in the supervised classification algorithm.The resulting classification maps should be checked using groundtruth information and field validation surveys if possible[2]. In general, supervised classifications are more accurate than unsupervised.

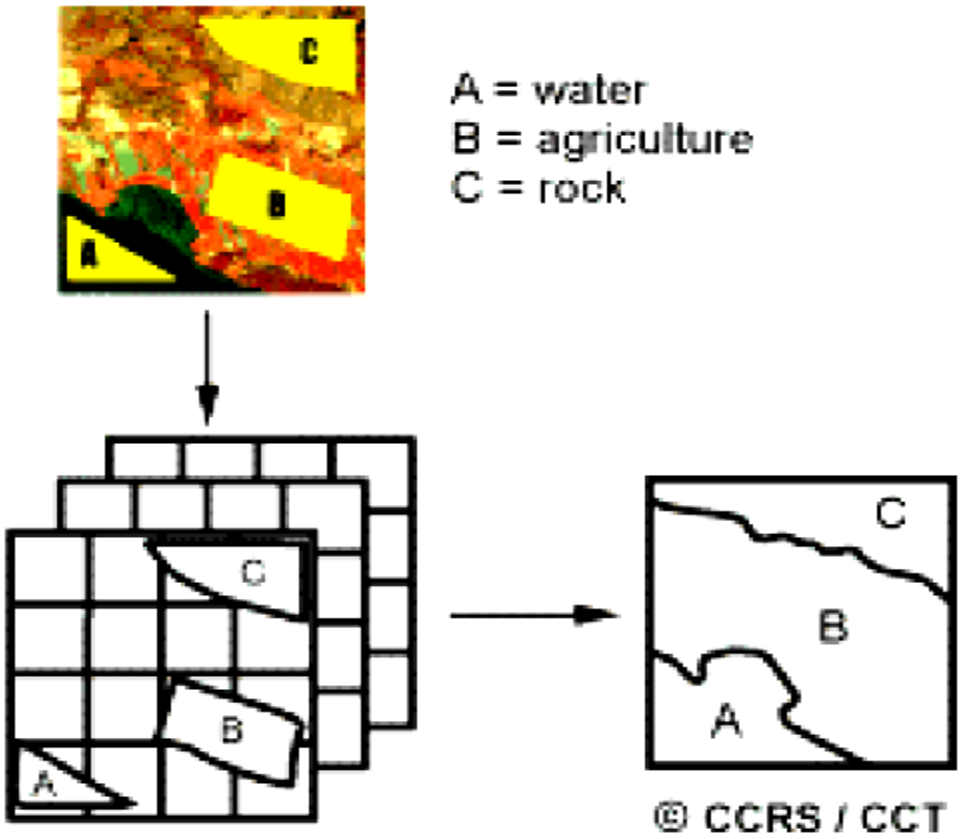

Figure 1.3: Supervised classification (From CCRS Website).

1.3.2 Unsupervised classification

Unsupervised classification does not start with a pre-determined set of classes as in a supervised classification. Unsupervised classification algorithms compare pixel spectral signatures to the signatures of computer determined clusters and assign each pixel to one of these clusters. Knowledge of the materials contained within the scene is not needed beforehand as the computer assesses the inherent variability and determines cluster identification. Classified distribution maps then require knowledge of the scene area in order to determine what each class (i.e. cluster) may represent in the real world (Figure 1.4). Clustering algorithms are used to determine the statistical structures in the data. Thus, unsupervised classification is not completely without human intervention. Lots of researchers are working in this area to develop human intervention-free unsupervised classification systems[2]. This is very interesting and is on-going area of research, and thus forms the basis of research proposed to be done through this synopsis.

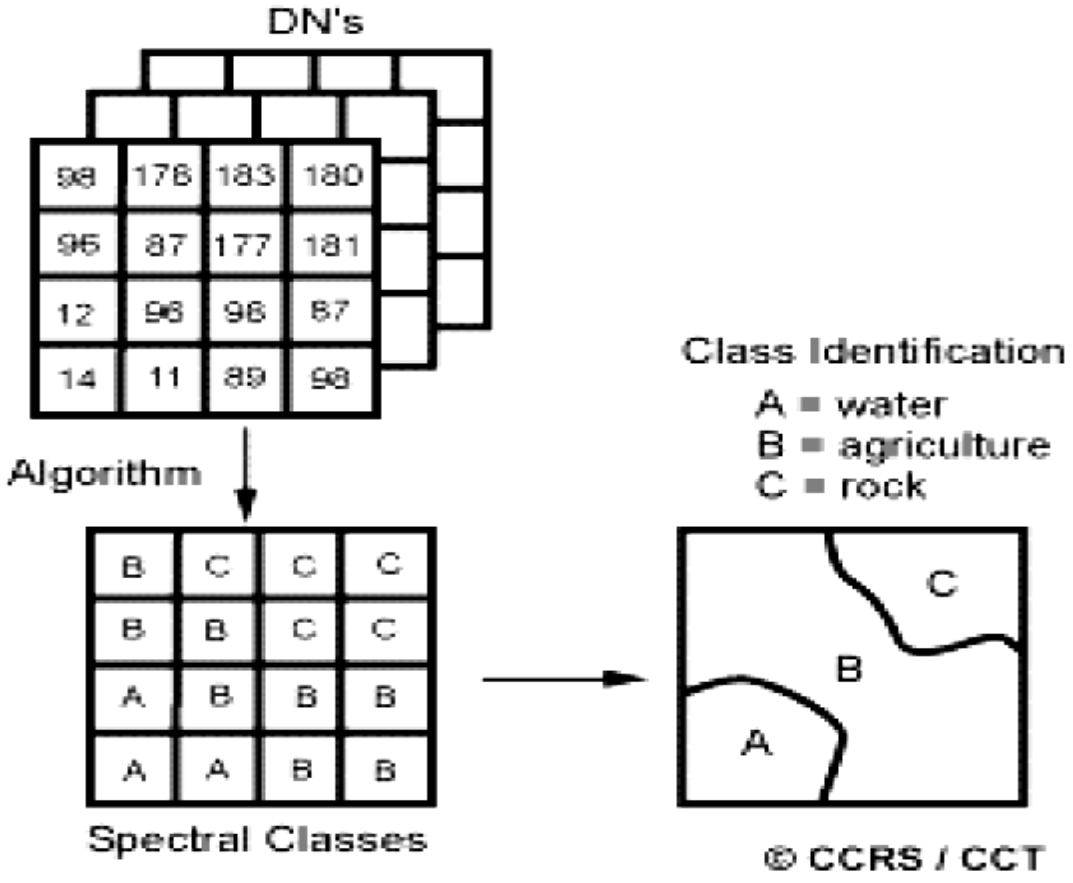

Figure 1.4: Unsupervised classification (From CCRS Website).

1.4 Introduction to change detection in images

Change processing on imagery data involves the detection of a set of pixels that have undergone a significant change relative in a previous data sequence. This change in time is typically referred to as temporal change and is performed as a systematic CD study involving two sets of data prepared at different times [20]. The changes may be due to object movement, insertion, deletion, removal or deformation, and the changes are usually affect the spectral signatures at same pixel locations of two sets of images of the same scene. Before analyzing CD it is essential the two sets of data are accurately registered. It is noted that registration accuracy of less than one-fifth of a pixel is required to achieve a CD error rate of less than 10%. The underlining fundamental assumption when applying any CD algorithm is that when there is a difference in spectral response of a pixel between images of two time lapse informatics, a change is detected. CD analysis typically generates a correspondence image from an image pair showing any changes. (Figure 1.5) Usually, in the comparison process, two corresponding pixels belonging to the same location in an image pair are determined on the basis of a quantitative measure. If this measure exceeds a predefined threshold a change is labeled. A binary image, B identifies the changed region, where

$$B(x) = \begin{cases} 1, \text{ if pixel corresponds a significant change} \\ 0, \text{ elsewhere} \end{cases} \quad (1)$$

Two images or set of images is the minimum requirement to identify change however the pair can be a successive series of images.

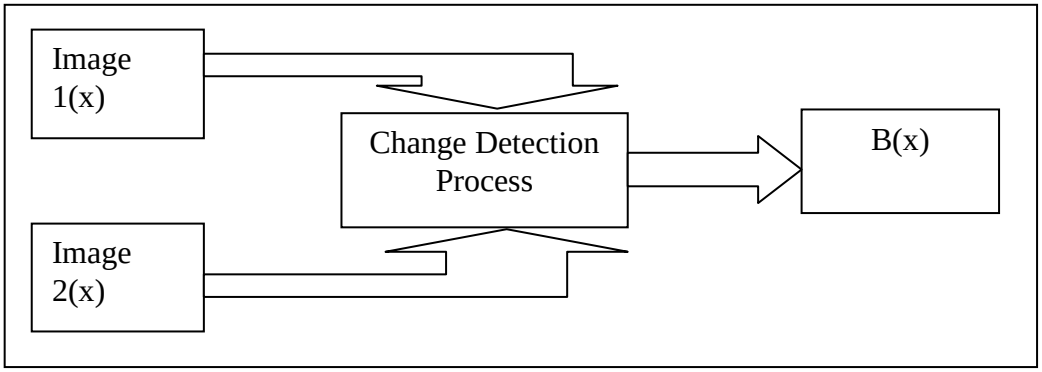

Figure 1.5: Change Detection Process.

Table 1.1: Variation of value of pixels in change detection.

B(*x*) Value	Description
1	If pixel *x* corresponds to a significant change from Im1(x) to Im2(x)
0	Otherwise

The decision at pixel *x* generally involves evaluating a cost function and selecting a suitable decision threshold. The estimation of the change mask involves a series of steps, presented in Figure 1.6. These steps involve: image pre-processing, feature extraction, dimension reduction, image comparison, decision rule application, and image post-processing.

Nevertheless, these steps are not necessarily performed by every change detection technique; it depends on the method used. Below, a general description of each change detection step is provided:

- **Image pre-processing**: In this step, the two images are compared in both the spatial and spectral domain. The two images should be co-registered so that pixels with the same coordinates in the image may be associated with the same area on the ground.
- **Feature extraction:** In this step, subset of new features is extracted from the original feature set. The features are extracted in such a way that maximum information may be kept in the new subset.
- **Dimension reduction:** As the original image has much dimensions so this step involves the representation of each image in a new space of lower dimension.

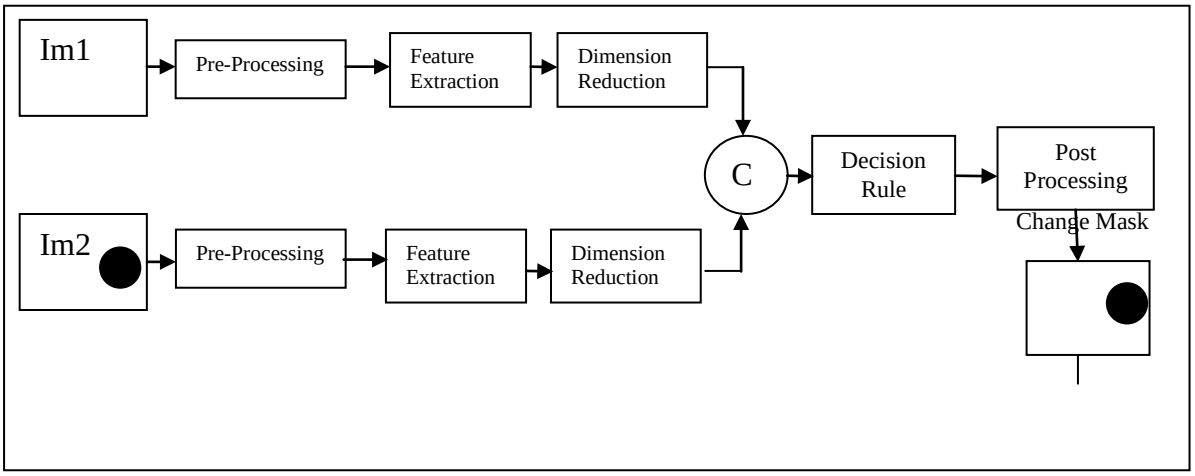

Figure 1.6: General steps for the estimation of the change mask.

By this, the change detection problem reduces to the comparison of the polynomial coefficients or the normal distributions, to determine if any change occurred.

- **Image comparison:** In this step, the two registered and corrected images or their representation are compared, pixel-by-pixel, in order to generate a further image. A comparison measure used widely because of its simplicity is image differencing.
- **Decision rule:** To detect the change among the images it is required to set a threshold. So, this step involves the selection of a threshold, to decide if a pixel has or has not change from one time to another.
- **Post-processing:** It may also be possible that the results obtained by change detection process are noisy. So a post processing step is needed when change detection results are noisy or inadequately smooth.

1.5 Change detection techniques

From the above made discussion, change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times. Change detection is an important process in monitoring and managing natural resources and urban development because it provides quantitative analysis of the spatial distribution of the population of interest.

More specifically, the change detection technique can be used to: 1) detect the changes that have occurred; 2) identify the nature of the change; 3) measure the area extent of the change; and 4) assess the spatial pattern of the change. A wide variety of digital change detection techniques have been developed over the last two decades. Typical examples include:

1. Image differencing
2. Image ratios
3. Conventional principal component analysis (PCA)
4. Change vector analysis (CVA)
5. Post classification comparison
6. Multivariate alteration detection (MAD)
7. Maximum likelihood correlation coefficient

Due to the importance of detecting changes in many fields, new techniques are being developed constantly for hypersperal imagery ; nevertheless the ones mentioned above, are the most commonly used with multispectral imagery. A description of these is mentioned below.

1.5.1 Image differencing

In this technique, images of the same area, obtained from times *t*1 and *t*2, are subtracted pixelwise. Mathematically, the difference image is

$$I_d(x, y) = I_1(x, y) - I_2(x, y) \quad (2)$$

Image differencing involves subtracting of the intensity values at same pixel locations of two images collected at two different periods of time. The two co-registered images are compared pixel-by-pixel and pixels associated with changed areas produce values significantly different from those pixels associated to unchanged areas. The subtraction usually results in positive and negative values in areas of change; and zero values in areas of no change in a new third image. Mathematically, it can be represented as:

$$B_{xy} = \begin{cases} 1 \ if \ |I_\lambda - I_{\lambda+1}| > Threshold \\ 0 \ otherwise \end{cases} \quad (3)$$

The third image or difference image is analyzed to obtain a change or no change classification by applying a threshold. The decision rule is the most critical step of any CD method. Only the pixels in the difference image above the threshold will correspond to a change at that location. After thresholding, a difference binary image (B_{xy}) is obtained, all pixels in which show change with a value 1 (white) and the pixels with no change have a value of 0 (black).

1.5.2. Image Ratios

Similar to image differencing, images are compared pixel wise in this method. Therefore, images must be registered beforehand. The ratio image, used in this method, is calculated by

$$Image\ Rationing = a\frac{I_\lambda}{I_{\lambda+1}} \quad (4)$$

In the above equation, the parameter, *a*, represents a possible scaling factor which can vary depending on the application. The ratio binary image is the new image of data created by the division of a set of bands for each pixel after a decision rule is introduced. Since values close to 1 correspond to no change, the algorithm must establish a multilevel threshold to determine where a change occurs. The disadvantage is that there is a possibility of division by zeros in this method [29]. However, this method has an important advantage that ratios minimize the variations in illumination. Both image differencing and image ratios are considered to be image algebra CD techniques because their basis is on mathematical manipulation.

1.5.3 Conventional principal component analysis (PCA)

Principal component analysis is a linear transformation technique and is the most common of the above mentioned techniques [31]. The main principal of the PCA approach is to use a set of images as input and to reorganize them via a linear transformation, such that the output images are linearly independent. The new coordinate system for the data is projected such that the greatest variance lies on the first axis or the first principal component and the second greatest variance on the second axis. In CD studies, the consequence of this linearization is that unchanged pixels or common information shared by a pair of images are expected to lie in a narrow elongated cluster along a principal axis equivalent to the first component (1PC). On the contrary, pixels containing a change would be more unique in their spectral appearance and would be expected to lie far away from this axis (2PC), as can be seen in Figure 7.

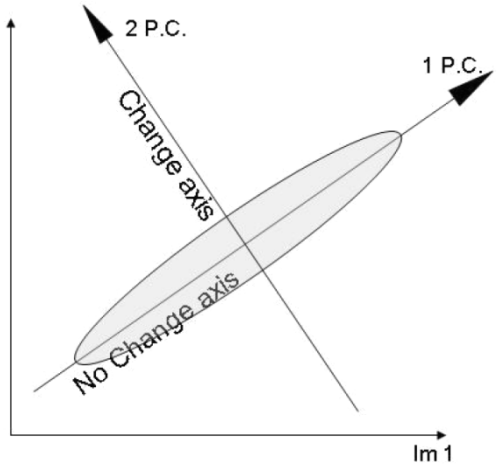

Figure 1.7: Change detection principle component analysis [24].

Thereby, the magnitude of change is quantified by the magnitude of the second principal component (2PC) given as $C_\lambda = e_{2,\lambda}^T(p_\lambda(:) - m_\lambda)$; where, $e_{2,\lambda}^T$ is the second eigenvector of the overall zero-mean covariance matrix and is given by:

$$C = \begin{bmatrix} \sigma_1^2 & \rho_{12}\sigma_1\sigma_2 \\ \rho_{12}\sigma_1\sigma_2 & \sigma_2^2 \end{bmatrix} \quad (5)$$

1.5.4 Change vector analysis (CVA)

Change Vector Analysis (CVA) is a technique where multiple image bands can be analyzed simultaneously [30]. As its name suggests, CVA does not only function as a change detection

method, but also helps analyzing and classifying the change. In CVA, pixel values are vectors of spectral bands. Change vectors (CV) are calculated by subtracting vectors pixel wise as in image differencing. The magnitude and direction of the change vectors are used for change analysis. The change vector can be formed as follows:

$$\Delta I(x,y,\lambda) = I_1(x,y,\lambda) - I_2(x,y,\lambda) = \begin{bmatrix} b_{11}(x,y,\lambda_1) - b_{12}(x,y,\lambda_1) \\ b_{21}(x,y,\lambda_1) - b_{22}(x,y,\lambda_1) \\ \vdots \\ b_{n1}(x,y,\lambda_1) - b_{n2}(x,y,\lambda_1) \end{bmatrix} \quad (6)$$

The next step in this technique is to calculate the magnitude of variation among spectral change vectors between the images pairs. The magnitude of the change vector is calculated by the Euclidean distance formula which measures the intensity of change.

$$\|\Delta I(x,y,\lambda)\| = \sqrt{(b_{11}(x,y,\lambda_1) - b_{12}(x,y,\lambda_1))^2 + \ldots + (b_{n1}(x,y,\lambda_1) - b_{n2}(x,y,\lambda_1))^2} \quad (7)$$

The angle of the vectors, which indicates the nature of change that occurred, varies according to the number of components used. In other words, each vector is a function of the combination of positive or negative changes through channels or spectral bands.

1.5.5 Post classification comparison method

This change detection method separately classifies multi-temporal images and then implements comparison of the thematic maps pixel by pixel . The advantages of this method it that it minimizes the impact of atmospheric, sensor and environmental effects between multi-temporal images and also provides a complete matrix of change information. In addition, there is no need of thresholding. However, it requires a large amount of time and expertise to create classification products and its final accuracy depends on the quality of each classified image. If a supervised classification technique is considered, sufficient training sample data for classification is required.

1.5.6 Multivariate alteration detection (MAD)

The multivariate alteration detection (MAD) method is based on a classical statistical transformation referred to as canonical correlation analysis [23]. Canonical correlations analysis investigates the relationship between two groups of variables. It finds two sets of linear combinations of the original variables, one for each group. The first two linear combinations are

the ones with the largest correlation. This correlation is called the first canonical correlation, and the two linear combinations are called the first canonical variates. The second two linear combinations are the ones with the largest correlation subject to the condition that they are orthogonal to the first canonical variates. This correlation is called the second canonical correlation, and the two linear combinations are called the second canonical variates. Higher-order canonical correlations and canonical variates are defined similarly. Because corresponding pairs of canonical variates are linear combinations of the original variables ordered by correlation or similarity between pairs, it seems natural to base a change detection scheme on differences between these pairs of variates. If the multispectral pixel intensities measured at two different times by random vectors X and Y can be represented as follows:

$$X = [X_1 \dots X_k]^T \quad (8)$$
$$Y = [Y_1 \dots Y_k]^T$$

Where, *k* is the number of spectral components, then linear combinations are calculated:

$$a^T X = a_1 X_1 + \cdots a_k X_k \quad (9)$$
$$b^T Y = b_1 Y_1 + \cdots b_k Y_k$$

Such that the difference of the transformed vectors has maximum variance:

$$\max\ (var\{a^T X - b^T Y\}) \quad (10)$$

Subjected to the constraints:

$$var\{a^T X\} = 1$$
$$var\{b^T Y\} = 1 \quad (11)$$

Under these constraints:

$$var\{a^T X - b^T Y\} = 2(1 - corr\{a^T X - b^T Y\}) \quad (12)$$

Since this method is used for change detection, it is requested that $a^T X$ and $b^T Y$ are positively correlated. Therefore, determining the difference between linear combinations with maximum variance corresponds to determining linear combinations with minimum (non-negative) correlation,

$$\min\ (corr\{a^T X, b^T Y\}) \quad (13)$$

This complies with canonical correlation analysis. Then the multivariate alteration direction is defined as:

$$\begin{bmatrix} X \\ Y \end{bmatrix} \rightarrow \begin{bmatrix} a_p^T X_p - b_p^T X_p \\ \vdots \\ a_1^T X_1 - b_1^T X_1 \end{bmatrix} \quad (14)$$

where, a_i and b_i are the defining coefficients from a standard canonical correlation analysis.

The first difference (with the variates $a^T X$ and $b^T Y$) shows maximum variation. The j^{th} difference (with the variates $a_{p-j+1}^T X$ and $b_{p-j+1}^T Y$) shows maximum variation subject to the constraint of being uncorrelated with the previous ones.

1.5.7 Maximum likelihood correlation coefficient

This approaches the maximum likelihood method to estimate the change parameter [32] incorporated in the joint conditional probability density function (PDF) of an image pair. The HSI cubes or frames are converted into long vectors and the measured reflectivity at pixel position n in two vector images are denoted by x_n and y_n. These measured values are represented by the models,

$$x_n = s_n + n_1 \quad (15)$$

$$y_n = \alpha s_n + \left(\sqrt{1-\alpha^2}\right) z_n + n_2 \quad (16)$$

Where, s_n denotes the true reflectivity and n_1 and n_2 are additive noise terms. The amount of change between the first image, x_n and the second y_n is given by α which ranges from 0 to 1. The random variable z_n is completely uncorrelated with s_i and it represents the change that has occurred. In vector notation, the observation can be written as,

$$\eta = \begin{bmatrix} x_n \\ y_n \end{bmatrix} = s_n \begin{bmatrix} 1 \\ \alpha \end{bmatrix} + z_n \begin{bmatrix} 0 \\ \sqrt{1-\alpha^2} \end{bmatrix} + \begin{bmatrix} n_1 \\ n_2 \end{bmatrix} \quad (17)$$

Under the assumption that the random variables have zero-mean, are Gaussian and are mutually independent; the conditional probability density function (PDF) follows as:

$$P\left(\frac{\eta}{\alpha}\right) = \frac{1}{\pi^2 |Q|} \exp\left(\eta' Q^{-1} \eta\right) \quad (18)$$

where,

$$Q = E\{\eta\eta'\} = \begin{bmatrix} \sigma_s^2 + \sigma_n^2 & \alpha\sigma_s^2 \\ \alpha\sigma_s^2 & \sigma_s^2 + \sigma_n^2 \end{bmatrix} \quad (19)$$

The maximum likelihood estimate is the value of α that maximizes equation 26; and is given by:

$$L = -cN\ln[\sigma_z^4(1-\alpha^2) + 2\sigma_n^2\sigma_z^2 + \sigma_n^4] - \sum_{n=1}^{N}\left[\frac{(x_n^2 - 2x_n y_n\alpha + y_n^2)}{(1-\alpha^2)\sigma_z^2}\right] \quad (20)$$

The next step in finding α that maximizes the above function is to differentiate this expression with respect to α and set to zero

$$\frac{\partial L}{\partial \alpha} = 2N\alpha\sigma_z^4 + \frac{2x_n y_n \alpha}{(\alpha^2-1)\sigma_z^2} + \frac{2(x_n^2 - 2x_n y_n\alpha + y_n^2)\alpha}{(\alpha^2-1)^2\sigma_z^2} = 0 \quad (21)$$

Solving the likelihood equation above for α yields the maximum likelihood coefficient used in CD. The Maximum likelihood estimator of α is given by:

$$\alpha_{ML} = \frac{2\sum_n x_n y_n}{\sum_n x_n^2 + \sum_n y_n^2} \quad (22)$$

1.6 Aim

To design and develop an algorithm for change detection in high resolution images and to assess its performance in terms of various parameters.

1.7 Research Objectives

1. To review the technologies and methodologies for change detection in high resolution images.
2. To investigate a strategy measure and generate alarms subject to the timings and extent of change detected.
3. To perform a pilot study trial of the developed model, aiming to investigate its efficiency in terms of various parameters such as robustness, false alarm generation and noise (e.g. speckle) tolerance.
4. To investigate the performance of developed system for the detection of change in different scenes in high resolution images.

2.1 Literature survey

Yuqi T. et. al. [1] in 2013 mentioned a novel change detection model that focuses on building change information extraction from urban high-resolution imagery. It consists of two blocks: 1) building Interest-point detection, using the morphological building index (MBI) and the Harris detector; and 2) multitemporal building interest-point matching and the fault-tolerant change detection. Experiments results show that the method was effective for building change detection from multitemporal urban high-resolution images. Moreover, the author also presented a comparison of the research method with the morphological change vector analysis (CVA), parcel-based CVA, and MBI-based CVA.

Bruno A. et. Al. [2] in 2013 discussed a nonparametric method for unsupervised change detection in multipass synthetic aperture radar (SAR) imagery. The discussed method starts from the scatter plot of the amplitude levels in the two images and applies the mean-shift (MS) algorithm to find the modes of the underlying bivariate distribution. The author assumed that if the two images have been preliminarily co registered and calibrated on one another, then all the modes lying outside the main diagonal correspond to the structural changes across the two observations. The value of the probability density function (PDF) in any of the off-diagonal modes found by the MS algorithm is translated into a value of conditional information. Thus, a feature is obtained on a per-pixel basis. The author also demonstrated the advantages over a preliminary version of the method without MS regularization and over another nonparametric method based on Kullback-Leibler divergence. The research is robust when it is applied to SAR images with different acquisition angles, whose effects are deemphasized, compared to the actual scene changes.

Chen W. et. al. [3] in 2013 mentioned a subspace-based change detection (SCD) method for hyperspectral images. Instead of dealing with band-wise changes, the research measures spectral changes. SCD regards the observed pixel in the image of Time 2 as target and constructs the background subspace using the corresponding pixel in the image of Time 1, and additional information. The subspace distance is calculated to determine whether the target is anomalous with respect to the background subspace. The anomalous pixels are then considered as changes. The author employed orthogonal subspace projection to calculate the subspace distance, which

makes full use of the advantage of the abundant spectral information in hyperspectral imagery, and is also easy to apply.

Jin Z. et. al. [4] in 2013 presented an approach for change detection in multitemporal synthetic aperture radar images. Considering about the existence of speckle noise, the author compared local statistics in a sliding window instead of pixel-by-pixel comparison. In each analysis window, the image is projected onto two vectors in two independent dimensions; thus, the pdf of each projection is closer to a Gaussian density. In order to measure the distance between the two pairs of projections, the research used a modified Kullback–Leibler (KL) divergence, called Jeffrey divergence. . The author conducted experiments on the real data to show that the detector outperforms all the others when a high detection rate is demanded.

Ping L. et. al. [5] in 2011 presented a semiautomatic approach based on object-oriented change detection for landslide rapid mapping . The methodology includes: 1) a fully automatic problem-specified multiscale optimization for image segmentation and 2) a multitemporal analysis at object level with several systemized spectral and textural measurements. The research first presented a problem-specific multiscale optimization of FNEA to reduce the degree of Over- and undersegmentation of landslides among a number of different scales .Second, The author presented a change detection using image transformation of PCA for a preliminary selection of landslide candidates from PC4 that removed false positives directly from PC2. Third, the matching image derived from SAM allowed the detection of subtle spectral changes from the change of spectrum vector direction. Fourth, spectral anomalies detected by RXD in the pre-event image allowed the removal of false positives, such as landslides that already existed before the landslide event. Finally, the author incorporated surface texture measures based on a 1-m LiDAR DTM were incorporated to remove false positives with low-frequency elevation variation. The author concluded that, for the case study in Messina, the research achieved user's and producer's accuracies of 75.9% and 69.9%, respectively, for the extent of landslides, and 81.8% and 69.5%, respectively, for the number of landslides.

Prashanth R. et. al. [6] in 2011 examined the effect of the prior elimination of strong changes on the results of change detection in bitemporal multispectral images using the previously published iteratively reweighted multivariate alteration detection (IR-MAD) method. An initial change

mask is calculated by identifying strong changes between two images. By using the mask and hence eliminating the strong changes from the analysis, the IR-MAD method is able to identify a better no-change background. It has been demonstrated that the IR-MAD algorithm can converge to a better no-change background even in the presence of huge changes by using the discussed initial change mask.

Joseph M. [7] in 2011 presented a physical model which explicitly accounts for shadow differences by incorporating shadow coefficients. Using this model, along with statistical noise assumptions, the change detection problem is formulated. The resulting Generalized Likelihood Ratio test (GLRT) provides an indicator of change for each pixel. The author applied the method to both synthetic and real imagery demonstrating some of the strengths and shortcomings of the approach. Only the false alarms resulting from shadow variation in the scene are discussed. The maximum likelihood estimates of the physical model parameters used for the GLRT are obtained from the entire joint data set to take advantage of coupled information existing between pixel measurements.

James T. [8] in 2010 derived a class of algorithms for detecting anomalous changes in hyperspectral image pairs by modeling the data with elliptically contoured (EC) distributions. These algorithms are generalizations of well-known detectors that are obtained when the EC function is Gaussian. The performance of these EC-based anomalous change detectors is assessed on real data using both real and simulated changes. The simulation results are compared with other algorithms. The author presented the mathematical analysis of the various distributions. In these experiments, the author showed that the EC-based detectors substantially outperform their Gaussian counterparts.

Turgay C. [9] in 2010 mentioned a novel method for unsupervised change detection in multitemporal satellite images by minimizing a cost function using a genetic algorithm (GA). The difference image computed from the multitemporal satellite images is partitioned into two distinct regions, namely, “changed” and “unchanged,” according to the binary change detection mask realization from the GA. For each region, the mean square error (MSE) between its difference image values and the average of its difference image values is calculated. The weighted sum of the MSE of the changed and unchanged regions is used as a cost value for the

corresponding change detection mask realization. The GA is employed to find the final change detection mask with the minimum cost by evolving the initial realization of the binary change detection mask through generations.

Turgay C. [10] in 2009 mentioned a novel technique for unsupervised change detection in multitemporal satellite images. The difference image is decomposed using S-levels undecimated discrete wavelet transform (UDWT). For each pixel in the difference image, a multiscale feature vector is extracted using the subbands of the UDWT decomposition and the difference image itself. The final change detection map is achieved by clustering the multiscale feature vectors using k-means algorithm into two disjoint classes: changed and unchanged. The author showed through the simulation results that the research performs quite well on combating both the zero-mean Gaussian noise and the speckle noise, which is quite attractive for change detection in both optical and SAR images.

Turgay C. [11] in 2009 mentioned a novel technique for unsupervised change detection in multitemporal satellite images using principal component analysis (PCA) and k-means clustering. The difference image is partitioned into h × h nonoverlapping blocks. S, $S \leq h2$, orthonormal eigenvectors are extracted through PCA of h × h nonoverlapping block set to create an eigenvector space. Each pixel in the difference image is represented with an S-dimensional feature vector which is the projection of h × h difference image data onto the generated eigenvector space. The change detection is achieved by partitioning the feature vector space into two clusters using k-means clustering with k = 2 and then assigning each pixel to the one of the two clusters by using the minimum Euclidean distance between the pixel's feature vector and mean feature vector of clusters. Experimental results confirm the effectiveness of the discussed research.

Michael T. et. al. [12] in 2008 discussed several insights into the nature of diurnal and seasonal change in hyperspectral imagery. The author also compared the capabilities of various predictive methods to suppress stationary background clutter and change detectors to find subtle target changes in the presence of such space-varying background change. The author mentioned that shadowing changes due to solar angle variations are probably the most prominent source of space-varying change in the collected data, but changes in vegetative state over long time periods

also seriously limit global linear predictors commonly used in change-detection algorithms. Segmented predictors, especially those based on quadratic clustering of the joint data, demonstrated a substantial improvement in both clutter suppression and change detection when coupled with a global AD.

Allan A. [13] in 2007 described new extensions to the multivariate alteration detection (MAD) method for change detection in bi-temporal, multi- and hypervariate data such as remote sensing imagery. The iteratively reweighted (IR) MAD method in a series of iterations places increasing focus on "difficult" observations, here observations whose change status over time is uncertain. The Author first describes the MAD method to calculate change from the images. The IR-MAD method first calculates ordinary canonical and original MAD variates. In the following iterations different weights to the observations are applied, large weights being assigned to observations that show little change, i.e., for which the sum of squared, standardized MAD variates is small, and small weights being assigned to observations for which the sum is large.

Thomas S. et. al. [14] in 2005 implemented a method which selects image-derived endmembers from high spatial and spectral resolution data enabling therefore certain surface features associated particularly to the wetland areas to be determined. The identification and application of selected endmembers is based on detailed data obtained at the field scale and related to the hyperspectral data. The spectral information contained in these endmembers was extrapolated to a temporal series of broadband multispectral imagery on which spectral unmixing analysis was performed in order to detect changes in the wetland over time. Results obtained showed that the selected wetland components have undergone important changes in both their total area as well as their spatial distribution. These changes are mainly associated with the anthropogenic impact; however, natural influences due to seasonal fluctuations may coincide with the overall changes, although this in general is difficult to determine. A major contribution of this work is the capacity to use endmembers derived from hyperspectral information in the analysis of existing multispectral data from different sensors.

Francesca B et. al. [15] in 2005 mentioned a novel approach to change detection in multitemporal synthetic aperture radar (SAR) images. The research exploits a wavelet-based multiscale decomposition of the log-ratio image aimed at achieving different scales (levels) of

representation of the change signal. For each pixel, a subset of reliable scales is identified on the basis of a local statistic measure applied to scale-dependent log-ratio images. The results prove that the research performs slightly better in terms of spatial fidelity and significantly increases the overall accuracy of the change-detection map.

Ola H. et. al. [16] in 2003 presented a object specific multiscale digital change detection approach. This research incorporates multitemporal SPOT panchromatic data, Object specific analysis (OSA), Object specific up scaling (OSU), Marker controlled watershed segmentation (MCS) and image differencing change detection. The author applied this framework to SPOT Pan data, image objects that have changed between registration dates can be identified and delineated at their characteristic scale of expression. The result of this is a multiscale change detection framework capable of detecting and delineating relevant changes automatically at their corresponding scale of expression. The author conducted the study in the forest region of Orebro Administrative Province, Sweden.

Teerasit K. et. al. [17] in 2002 mentioned the problem of image change detection (ICD) based on Markov random field (MRF) models. The optimum ICD algorithm under the maximum a posteriori (MAP) criterion is developed under this model. The algorithm involves the search for an optimum for which the SA algorithm is used. By means of two examples, the author has shown the superior performance of our algorithm. The effect of uncertainties on the performance of algorithm were also investigated. The author found the algorithm to be quite robust to various types of uncertainties.

Geoffrey G. et. al. [18] in 2001 presented an algorithm as the solution to an approximate maximum likelihood (ML) image segmentation problem. Gaussian spectral clustering is used to model the scene background. A digital site model is constructed that contains image segmentation maps and extracted object features. Object-level change detection (OLCD) is accomplished by comparing objects extracted from a new image to objects recorded in the site model. A restricted implementation of the architecture is described and tested on long-wave infrared hyperspectral imagery. The author demonstrated that spectral OLCD can eliminate false alarms based on their multitemporal persistence. Incorporating multiple images in the site model is observed to improve OLCD performance.

Takahiro Y. et. al. [19] in 2001 mentioned the detection of the temporal changes using three-dimensional (3-D) segmentation. The discussed method is a clustering methods for temporal changes. In the presented method, multitemporal images form a image block in 3-D space; – plane and time axis. The image block is first divided into spatially uniform sub-blocks by applying binary division process. The division rule is based on the statistical -test using Mahalanobis distance between spatial coefficient vectors of a local regression model fitted to neighboring sub-blocks to be divided. The divided sub-blocks are then merged into clusters using a clustering technique. The author mentioned that, the block-based processing, like the spatial segmentation technique, is very effective in reduction of apparent changes due to noise. Temporal change is detected as a boundary perpendicular to the time axis in the segmentation result. The research is successfully applied to actual multitemporal and multispectral LANDSAT/TM images.

Daniel T. et. al. [20] in 2000 mentioned a method for motion detection that is considerably less sensitive to time–varying illumination. The research is based on combining a motion detection algorithm with a homomorphic filter which effectively suppresses variable scene illumination. The author discussed that the detection of changes in the reflectance component is directly related to scene changes, i.e. object motion. The author discussed that the results obtained from test image sequences with genuinely varying illumination confirm that homomorphic motion detection is insensitive even to fast variations in illumination, without noticeably harming the detection of moving objects. A comparison of the research with the other alternative techniques is also discussed. A limitation of the research is the assumption of spatially slowly-varying illumination.

Lorenzo B. et. al. [21] in 2000 presented a supervised nonparametric technique, based on the “compound classification rule” for minimum error, to detect land-cover transitions between two remote-sensing images acquired at different times. In the obtained rule, based upon the probabilities of transitions, the temporal dependence between two images is discussed.The author mentioned an iterative algorithm which allows the probabilities of transitions to be estimated directly from the images under investigation. The author showed through the experimental results on two Thematic Mapper images that the research provides remarkably

better detection accuracy than the “Post-Classification Comparison” algorithm, which is based on the separate classifications of the two images.

Sze C. et. al. [22] in 1998 mentioned an illumination-independent statistical change detection method. The research consists of two parts. First, based on defined circular shift moments, it is discussed that the structural changes can be distinguished from those due to time-varying illumination in the noise-free case. Second, in the light of the characteristics of the defined moments, a statistical decision rule is also discussed to cope with the effects of noise. The author presented the experimental results which indicate that the research detects changes accurately in the time-varying illumination case.The author concluded that SCSM algorithm is accurate and robust for change detection in practical applications.

Allan A. et. al. [23] in 1998 introduced the Multivariate Alteration Detection (MAD) transformation which is based on the established canonical correlation analysis. The research also discussed postprocessing of the change detected by the MAD variates using maximum autocorrelation factor (MAF) analysis. The MAD and the combined MAD/MAF transformations are invariant to linear scaling. The author also described the other multivariate change detection schemes like principal component analysis. The algorithm was simulated by using AVHRR and Landsat MSS data. The author also discussed the groundtruth data to detect and compare the changes.

Rafael W. et. al. [24] in 1997 mentioned a change detection strategy which integrates various concepts in order to make change detection robust against varying recording conditions, to utilize additional spatial features from local neighborhoods, and to enable unsupervised change detection. The study considered change detection as an unsupervised classification problem with the two classes 'Change' and 'No Change’. The decision was made using Bayes Rule, which minimizes the probability of error. Firstly, the robust change detection by iterative principal component transformation is presented. The results show the locations of 'Change' -areas, and probability images giving the Bayesian probability of 'Change' versus 'No Change' for each pixel.

Lorenzo B. et. al. [25] in 1997 mentioned a supervised nonparametric technique, based on the “compound classification rule” for minimum error, to detect land-cover transitions between two remote-sensing images acquired at different times. The research transform the compound

classification rule into a form easier to compute. In the obtained rule, probabilities of transitions is discussed, which take into account the temporal dependence between two images. The author discussed an iterative algorithm which allows the probabilities of transitions to be estimated directly from the images under investigation. Finally, the experimental results on two Thematic Mapper images are discussed which confirm that the discussed algorithm may provide remarkably better detection accuracy than the "Post-Classification Comparison" algorithm.

Pol R. et. al. [26] in 1996 presented a discussion about the methods and results of digital change detection primarily in temperate forest ecosystems. Two major components are discussed. First, the different perspectives from which the variability in the change event has been approached are summarized, and the appropriate choice of digital imagery acquisition dates and interval length for change detection are discussed. In the second part, preprocessing routines to establish a more direct linkage between digital remote sensing data and biophysical phenomena, and the actual change detection methods themselves are reviewed and critically assessed. Authors presented a case study of temperate forests (north-central U.S.A.) then serves as an illustration of how the different change detection phases discussed in this research can be integrated into an efficient and successful monitoring technique. Lastly, new developments in digital change detection such as the use of radar imagery and knowledge-based expert systems are highlighted.

John R. et. al. [27] in 1992 evaluated the impact of misregistration of images on the detection of changes in land cover using spatially degraded Landsat MSS images. The author focused the attention on simulated images of the normalized difference vegetation index (NDVI) at two of the spatial resolutions of the planned Moderate Resolution Imaging Spectrometer (MODIS), namely 250 and 500 m. In the first of two sets of experiments single date images from seven diverse areas were first misregistered against themselves and the statistical properties of the differences were analyzed using semivariograms. The author discussed that in the absence of any actual changes to the land surface, the consequences of misregistration were very marked even for subpixel misregistrations. Pairs of images from different time periods were then misregistered. The author showed that for four of the seven areas, an error equivalent to greater than 50% of the actual differences in the NDVI as measured by the semivariance, was induced by a misregistration of only one pixel. To achieve an error of only 10%, registration accuracies of 0.2 pixels or less are required.

Kurt K. et. al. [28] in 1989 presented two techniques for change detection where illumination is not assumed to be constant. The author discussed the description of the various new methods like the derivative model method and the shading model method. The author also used image pairs to present the results of all the techniques. From the results, the author concluded that the performance of the shading model method on sequences with no change in illumination is quite good. The author compares the results with the other techniques. From the comparison, the author concluded that when confronted with a change in illumination, this technique performs better than the D-method and the gray scale equalization technique and, certainly, significantly better than any of the other techniques.

3.1 Motivation

From the literature survey, the term change detection refers to the problem of identifying regions in a series of images taken at various time intervals. The time interval varies depending on the application and can go from seconds to even years. The most common application of change detection is remote sensing; which also forms the basis of the research reported to be done through this synopsis. The key challenges in this area are camera motion, noise and the parallax artifacts caused by the static objects having considerable height, such as due to the presence of buildings, trees and walls, from the difference image. These images can be hyperspectral or multi-spectral. The images may either be taken in very small interval, like many images in a day, or may be taken at a much larger time interval; therefore, a major challenge is how to separate normal changes (e.g. shadow and the effect of seasonal changes of background vegetation) from real changes caused by agricultural/industrial activities. This is a very practical problem and in addition, this phenomenon is random. Also, as far as hyperspectral images are concerned, most of the research uses only some bands to detect the changes. So this loses the generality of using the spectral changes by including all the spectral bands. From the literature survey, it is still found to be an active part of research. These practical problems interested a lot to authors; and therefore, provide motivation to carry on research in this domain of change detection.

3.2 Overview of problem

From the literature survey, it is found that several types of change detection techniques have been developed to date. Most of these are application specific; and broadly these all can be divided into two categories: supervised and unsupervised change detection. More specifically, both these techniques typically involve two steps: first an image registration is performed, then the aligned input image pair is segmented into changed (foreground) objects and background. However, these steps cannot be separated. It is because registration has a crucial impact on the extraction of changed image regions as well as an accurate registration would require the knowledge of changes. In recent years, the unsupervised change detection methods are highly preferred. However, the existing methods (with some discussed above) have been reported to give high false alarms and are less robust with high complexity. Therefore, the overall goal of the research work to be done through this synopsis is to develop efficient probabilistic methods for the unsupervised change detection problems in remote sensing by taking a novel approach which

simultaneously register and segment the changed regions. For this purpose, various image features will be considered for reliable change detection. It is expected that this will be beneficial for detecting changes over a longer time period.

3.3 Research methodology

The major steps involved to achieve the above given are summarized in Figure 19 and are detailed below.

- A detailed review of current change detection technologies/approaches in high resolution images and their limitations in meeting the requirements of future change detection will be done. A pilot stage study has been reported through literature review presented above. This study provided an overview of the research needs. More specifically, this study has justified the requirement of an algorithm based on pixel-by-pixel change detection approach in meeting the requirements of change detection in high resolution images.
- Following the review, the key existing change detection algorithms (such as Image rationing, Image differences and MAD etc.) will be implemented in MATLAB and their performance will be evaluated in terms of accuracy of changes detected, false alarms, robustness and other parameters. With this study, a detailed list of research needs will be produced.
- A strategy and thereafter an algorithm will be developed to do unsupervised change detection in high resolution images. The basis of this strategy will be to measure changes in high resolution images and then generate alarms subject to the timings and extent of change detected. The algorithm will monitor and record the changes detected, and compare the extent of change detected with a threshold value; to generate warning alarms. The number and rate of change of events per unit time and per unit pixels will be evaluated. The number of incorrect pixels selected and thus giving false alarms will also be investigated. The ability of the algorithm to tolerate various artificial and natural sources of noise (e.g. speckle) will be investigated. The model to be developed should be generic so that it can be applied with minimal and/or no change to different scenes (e.g. vegetation and landslides) in high resolution images. This will help to gain new insights to analyze the feasibility of practically realizing and implementing a change detection algorithm.

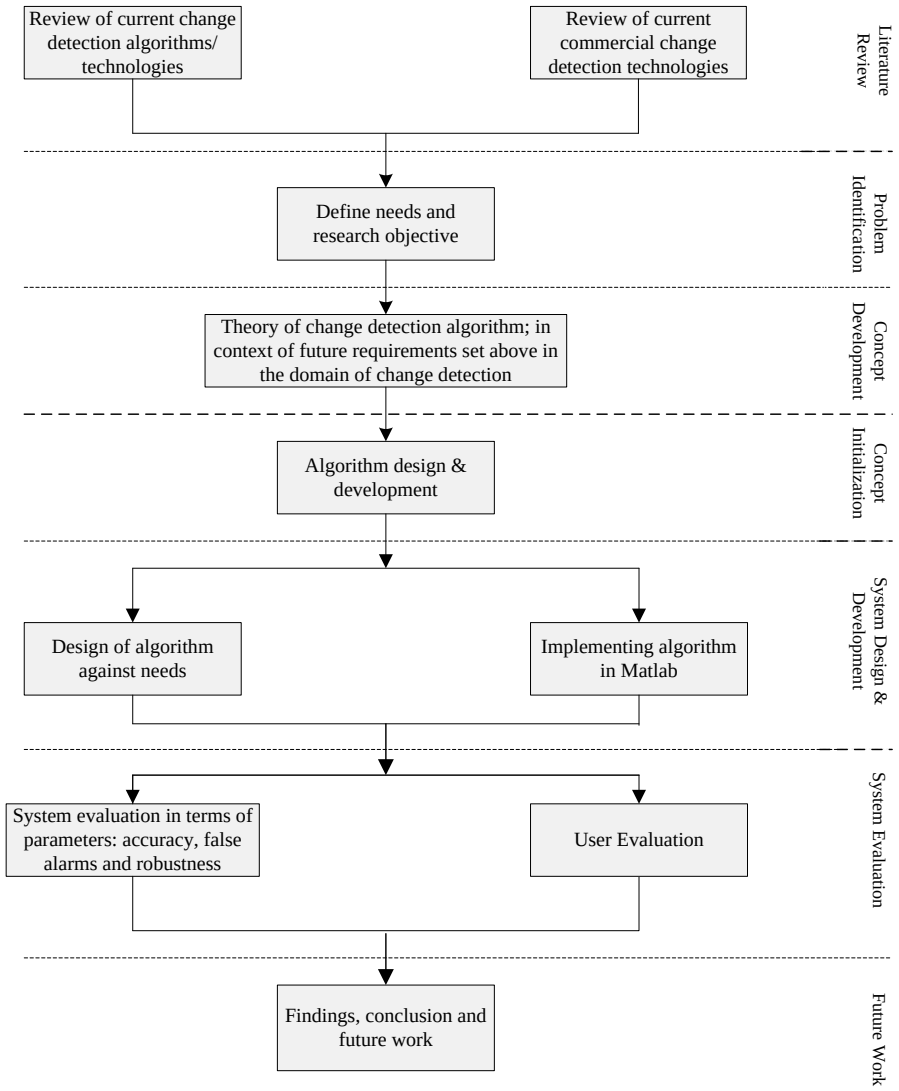
Review of current change detection algorithms/ technologies
Review of current commercial change detection technologies
Literature Review
Define needs and research objective
Problem Identification
Theory of change detection algorithm; in context of future requirements set above in the domain of change detection
Concept Development
Algorithm design & development
Concept Initialization
Design of algorithm against needs
Implementing algorithm in Matlab
System Design & Development
System evaluation in terms of parameters: accuracy, false alarms and robustness
User Evaluation
System Evaluation
Findings, conclusion and future work
Future Work

Figure 3.1: Overview of research design approach and methodology.

3.4 Thesis Time Frame

Table 3.1: Time required for completing the research work

Sr. No.	Research Work	Time Required
1	Literature Review	6 Months
2	Problem Identification	2 Months
3	Concept Development	4 Month
4	Concept Initialization	6 Month
5	System Design and Development	6 Month
6	System Evaluation	6 Month
7	Thesis binding and Publication	6 Month

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